Verification of a Satellite Observing Event-Based Sensor Model

A Examination

Rachel Oliver

31 August 2022

Space Domain Awareness (SDA)

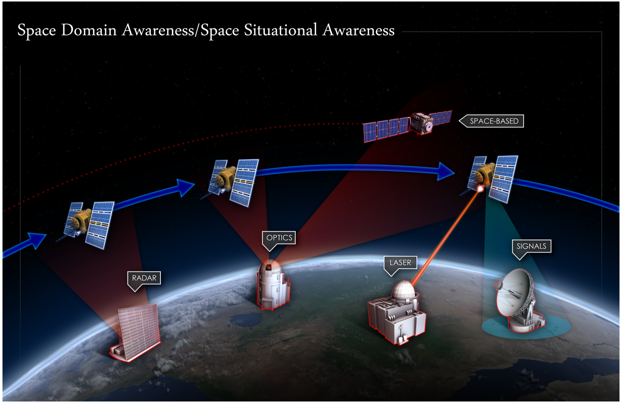


Figure: Weisbarth, 2020,
https://media.defense.gov/2020/Mar/15/2002264814/-1/-1/0/190111-F-HF064-002.PNG

Figure: MDA, 2008,
http://www.mda.mil/mdalink/pdf/too164.pdf

Growing Complexity

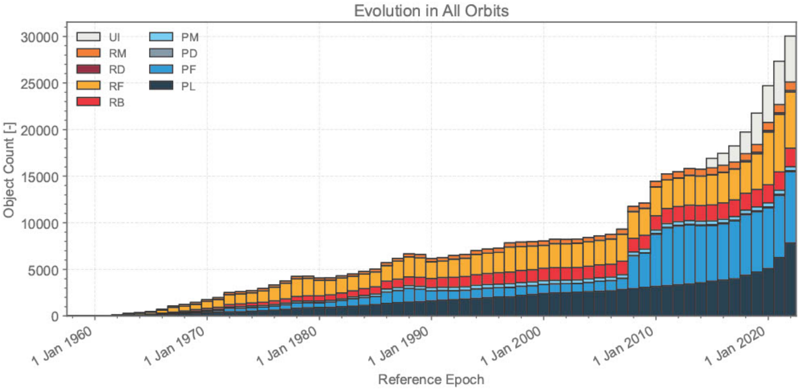
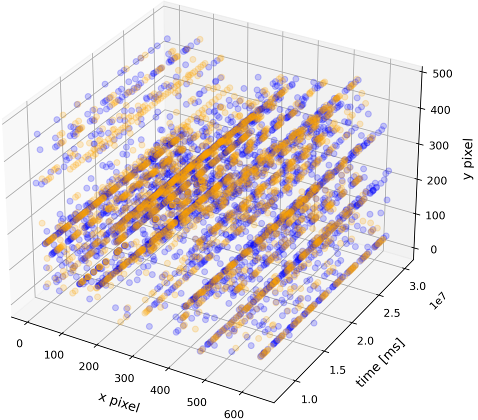


Figure: ESA, ESA's Space Environment Report, 2022

Event-Based Sensors



- Asynchronous data collection
- Records time series events, e
  - $e = \{t, x, y, \rho\}$
  - recording timestamp, t
  - pixel location, x and y
  - change polarity, ρ

Event-Based Sensors Advantages in SDA

- Event-Based Sensor Advantages for SDA
    - Temporal Sensitivity
    - High Dynamic Range
    - Space-Based
        - Low SWaP for Space-Based
        - Maximize Information for Downlink
        - Enable Onboard Computation
    - Ground-Based
        - Low Cost for Augmenting SDA Operations

Figure: Cohen, 2019, http://greg-cohen.com/project/astrosite/

Event Simulations

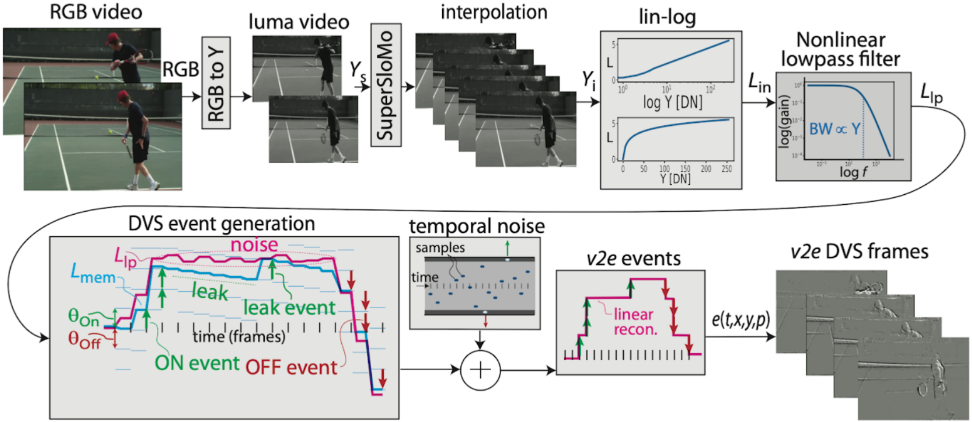
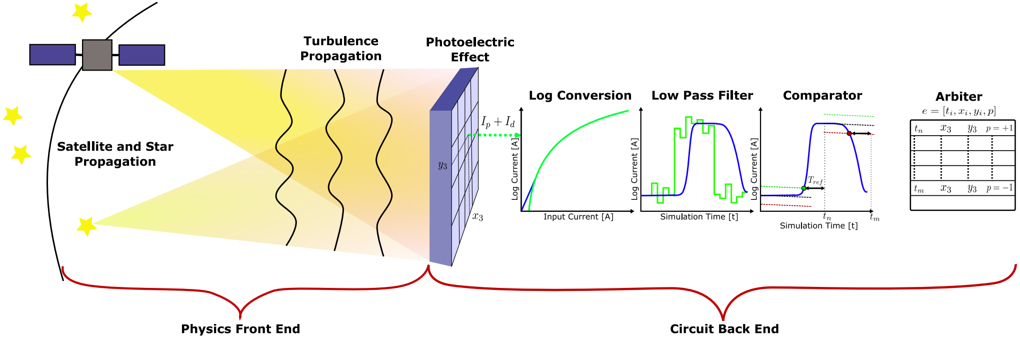


Figure: Delbruk, 2021, `https://sites.google.com/view/video2events/home`

New Event-based Sensor Model



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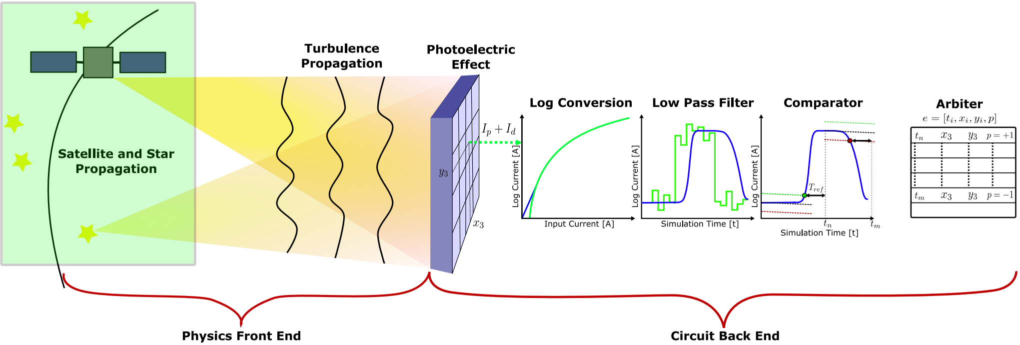
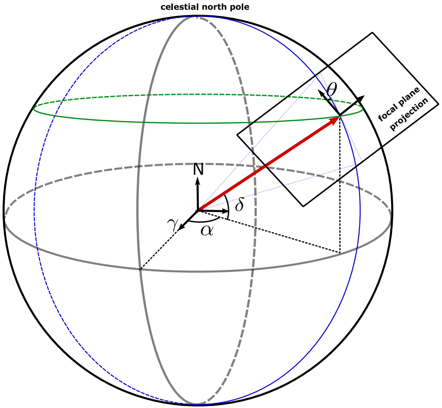
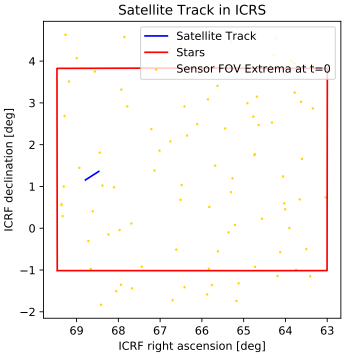


Satellite and Star Generation





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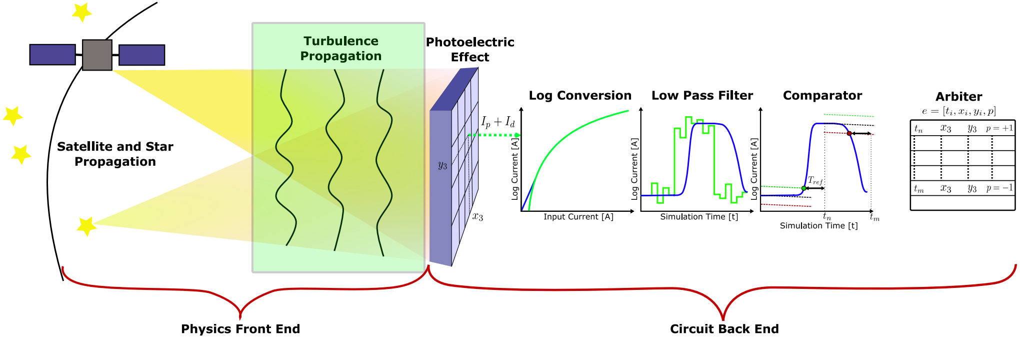
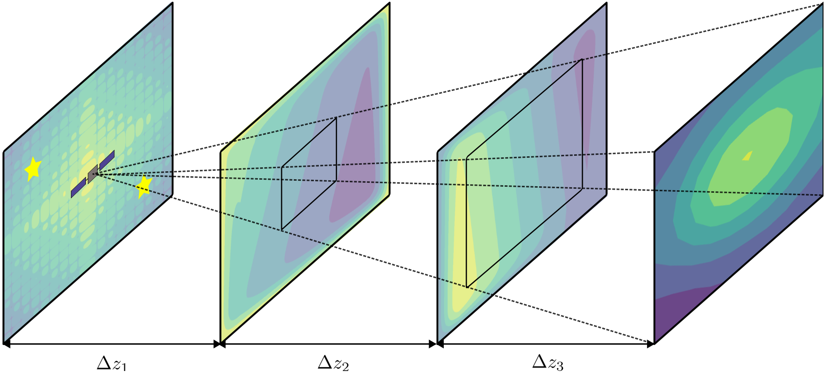


Simulating Atmospheric Propagation



$$U(r_n) = \mathcal{Q}\left[\frac{m_{n-1}-1}{m_{n-1}\Delta z_{n-1}}, r_n\right] \times \prod_{i=1}^{n-1}\left\{\mathcal{T}[z_i, z_{i+1}]\mathcal{F}^{-1}\left[f_i, \frac{r_{i+1}}{m_i}\right]\mathcal{Q}_2\left[-\frac{\Delta z_i}{m_i}, f_i\right]\mathcal{F}[r_i, f_i]\frac{1}{m_i}\right\} \times \left\{\mathcal{Q}\left[\frac{1-m_1}{\Delta z_1}\right]\mathcal{T}[z_1, z_2]U(r_1)\right\}$$

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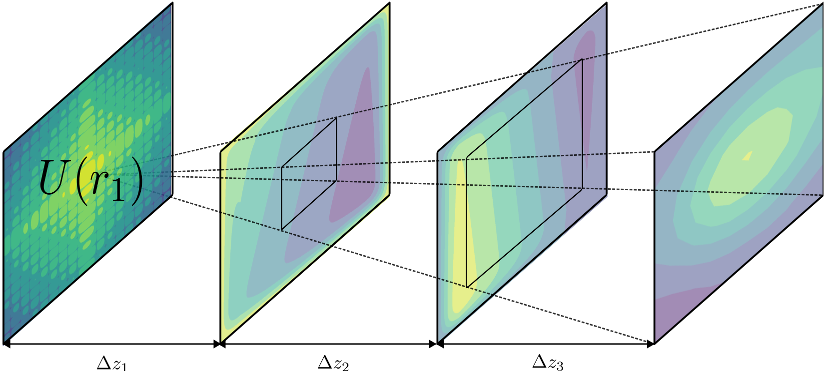

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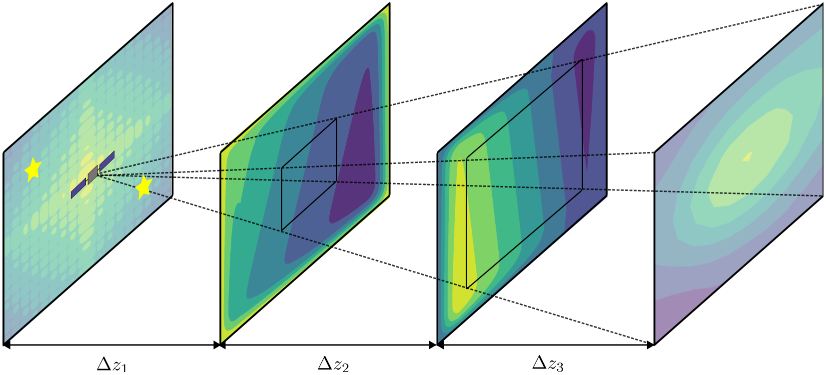

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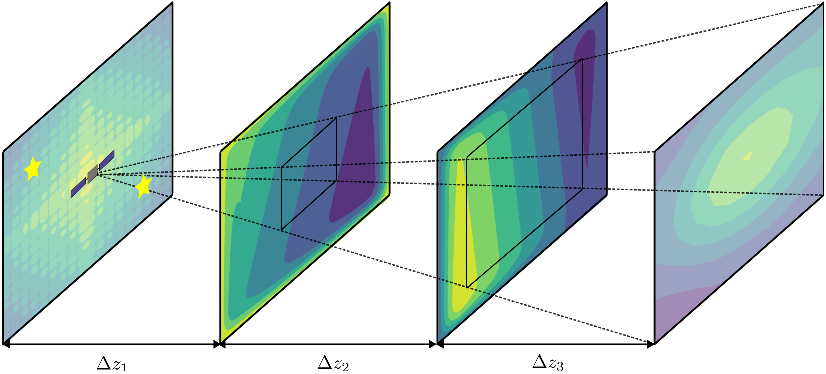

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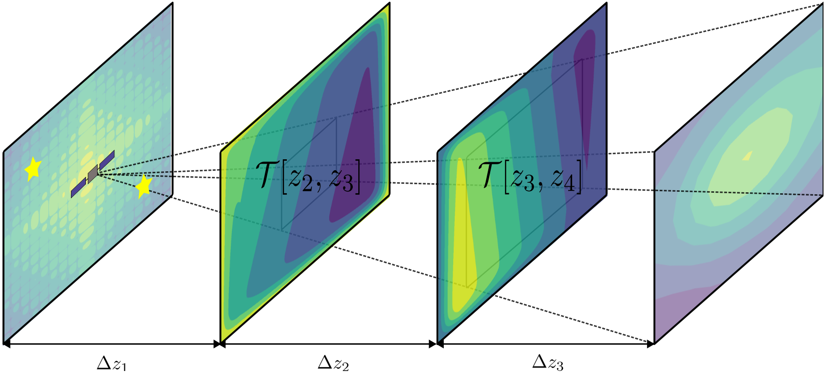

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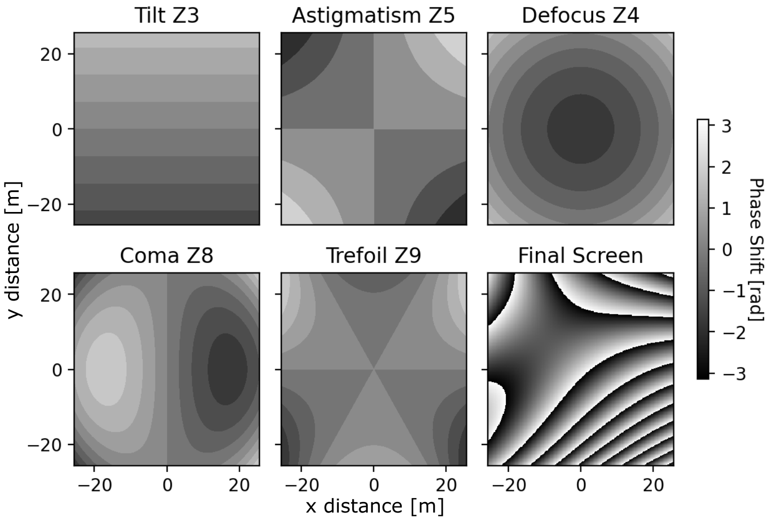
Zernike Mode Phase Screen



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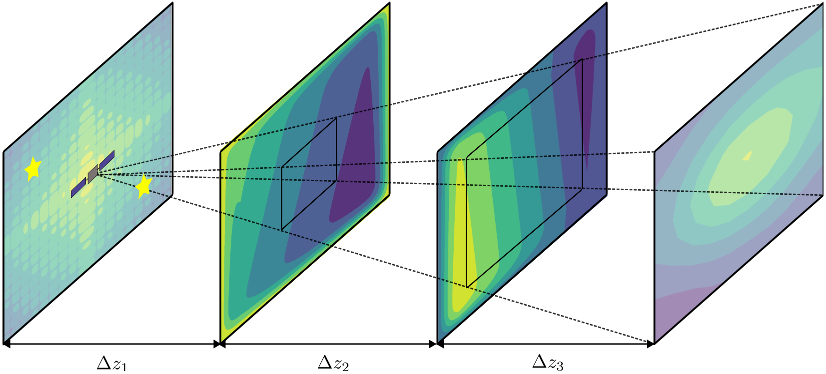

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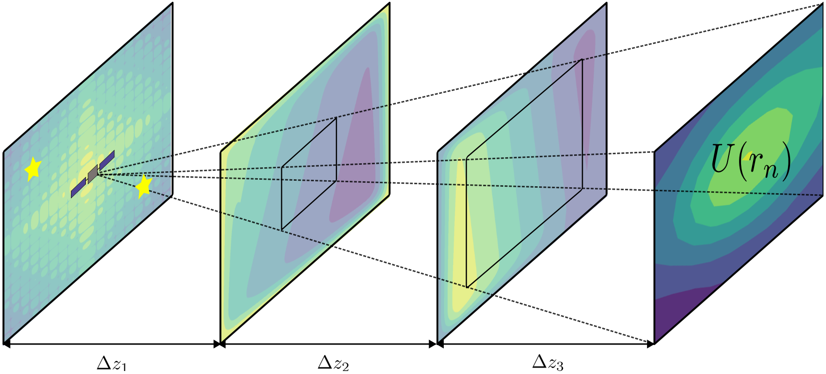

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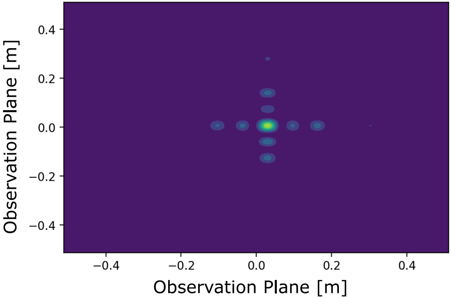
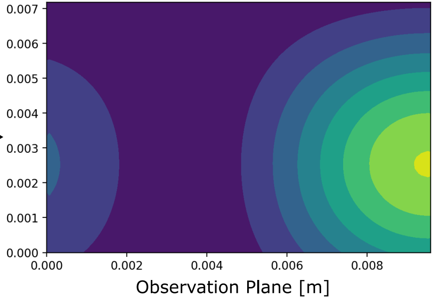
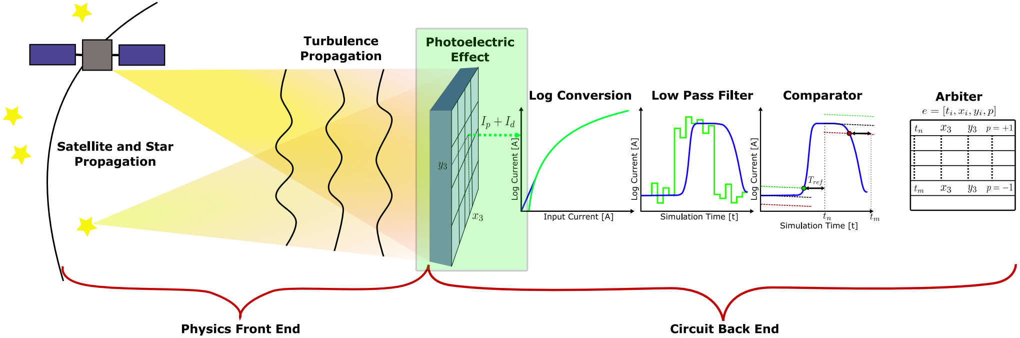


$$g_2 = g_1 \circledast h$$



New Event-based Sensor Model



Induced Photocurrent

- Responsivity linearly scales Power, $\Phi[W]$

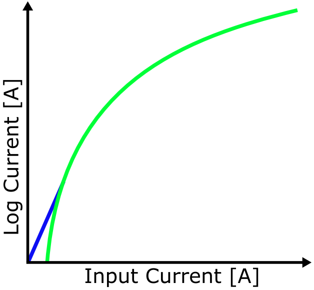
$$I_p = R_\lambda \Phi [A]$$

- Responsivity, R_λ, Scaled by Quantum Efficiency, η

$$R_\lambda = \eta \frac{q}{hf} \approx \eta \frac{\lambda}{1.23985} \left[\frac{A}{W} \right]$$

- Temperature, T, Dependent Dark Current, $I_{darklog}$

$$I_{darklog} = \ln(I_{dark}) = constant - \frac{E_a}{kT}$$



Event Simulations

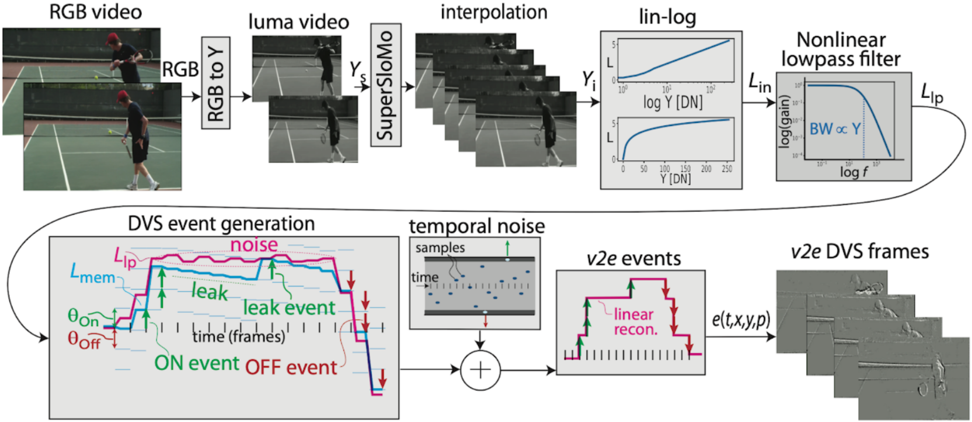


Figure: Delbruk, 2021, https://sites.google.com/view/video2events/home

Gaussian White Noise

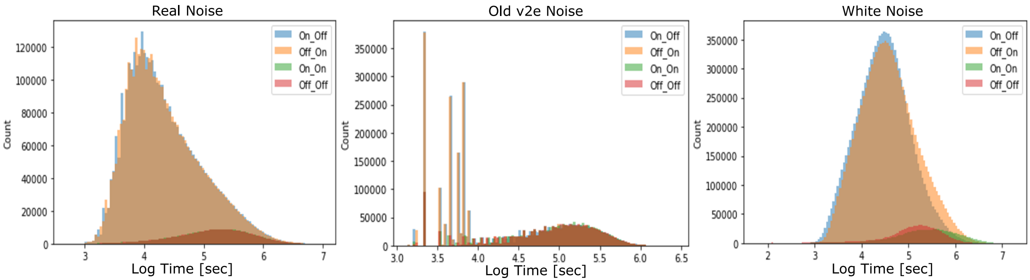


Figure: McRenyolds, 2022, ETH Zurich

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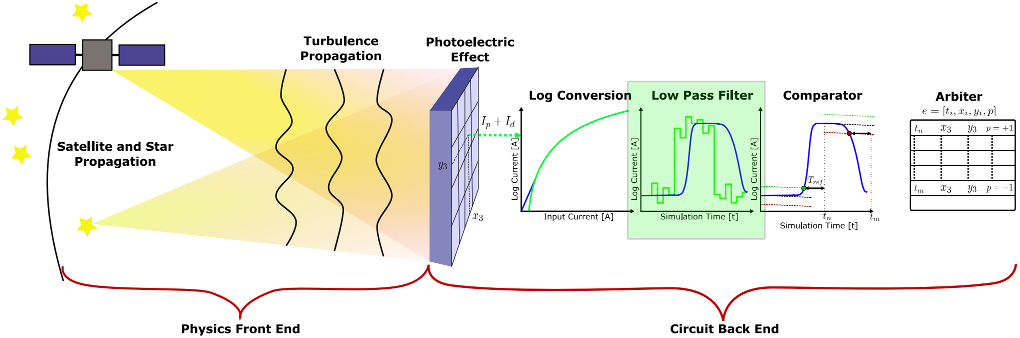


Low Pass Filter

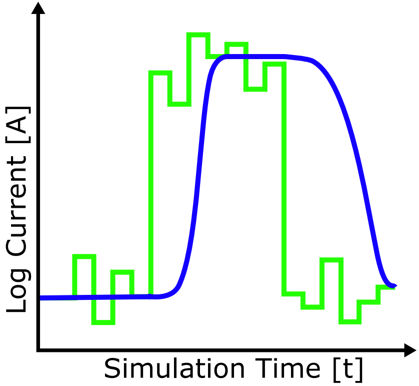
- Maximum bandwidth, $f_{3dBmax} \approx 3000[Hz]$
- Resultant bandwidth, f_{3dB}

$$f_{3dB} = \frac{I_{in} + (\frac{I_{max}}{10})}{I_{max}} \times f_{3dBmax}$$

$$\epsilon = e^{2\pi * \Delta t f_{3db}}$$

$$I_{p_{int}} \longleftarrow (1-\epsilon)I_{p-1} + \epsilon I_{in}$$

$$I_p \longleftarrow (1-\epsilon)I_{p_{int}} + \epsilon I_{in}$$



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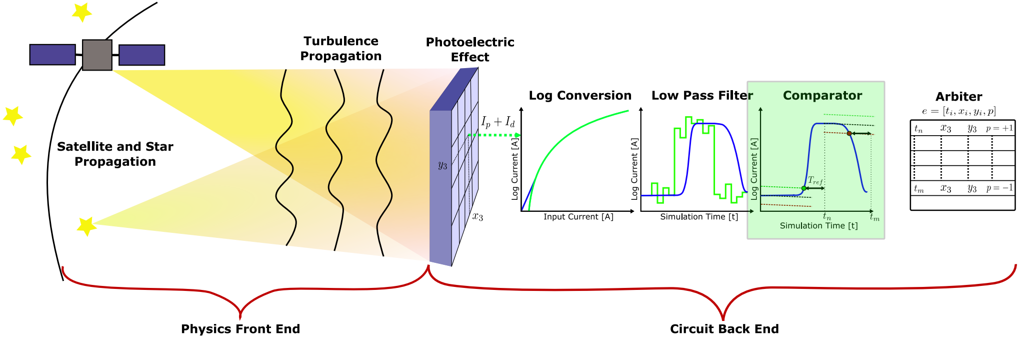
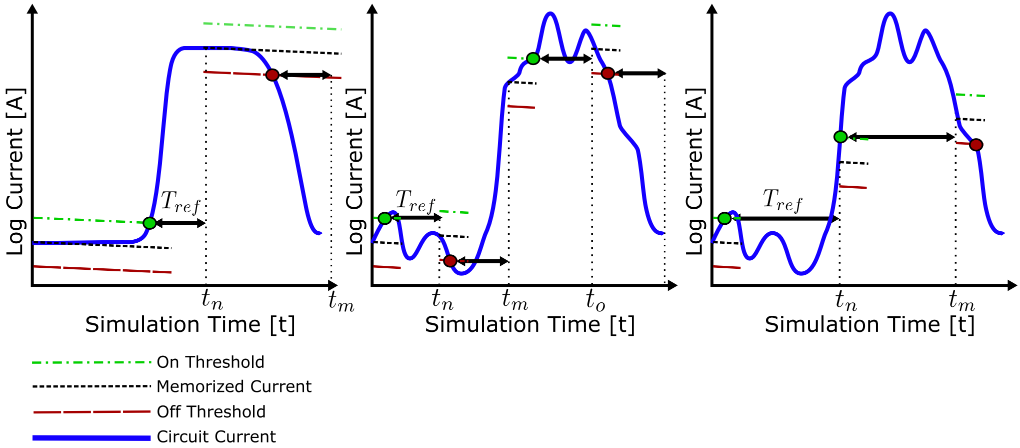


Comparator and Refractory Circuit



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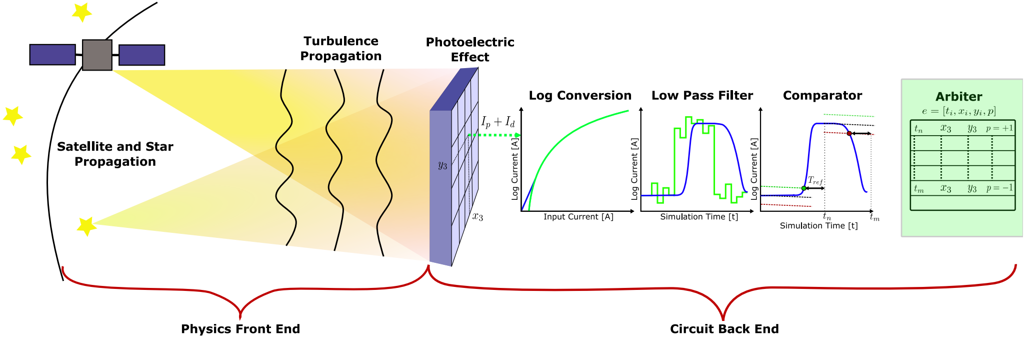
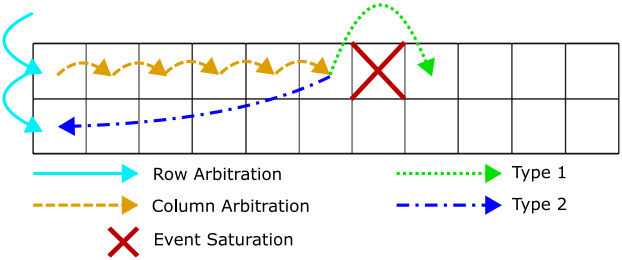


Arbitration

- Ordered row then column query
- Restricted maximum number of events
- Allows and tracks loss of events
    - Saturation
    - Refractory Period



Model Overview

- High Fidelity Model Innovations
  1. Inclusion of a physics based front end
  2. Induced current a function of quantum efficiency
  3. Inclusion of a temperature dependant dark current
  4. White noise scaled by photocurrent
  5. Realistic arbitration
  6. Tracks events lost during arbitration

Verification

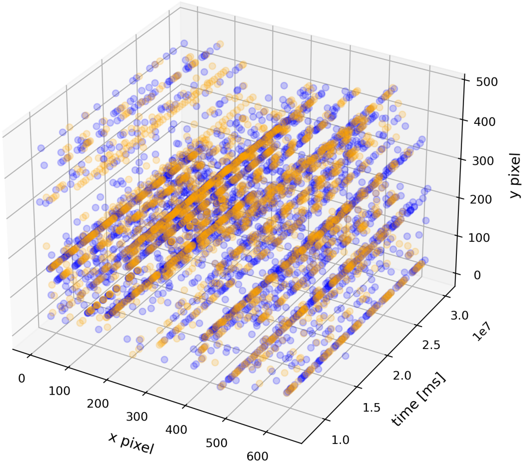
- Goal: Prove Model Creates Data Analogous to Real Data
  - Build trust in simulation output
  - Produce simulated data for algorithm development
  - Test camera settings and designs to maximize low-light performance
- Challenges:
  - Non-deterministic: no one-to-one matching
  - Unknown importance of data characteristics

Data Collection

- Prophessee Gen3 (VGA) camera
- 85mm f1.4 Lens
- January - March 2021
- Collection Procedure
  1. Slew to fixed azimuth and elevation
  2. Stare in fixed position for 30 seconds
  3. Slew to next location
- Courtesy of Dr. David Monet of AFRL Space Vehicles Directorate

Figure: Sony Prophesee, 2022 `https://www.prophesee.ai/event-based-evaluation-kits/`

Example Data

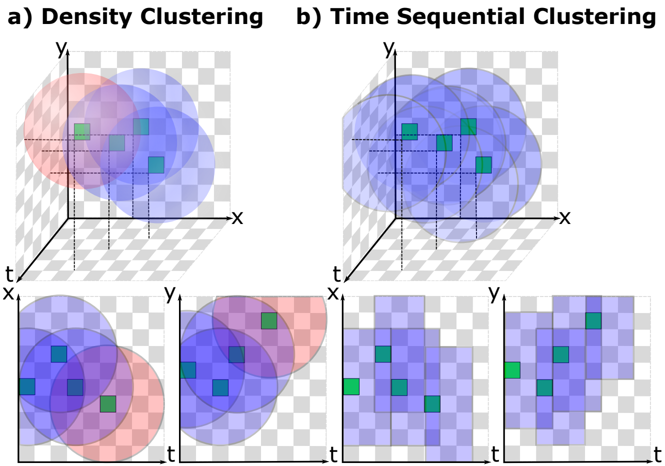


Analysis Approaches

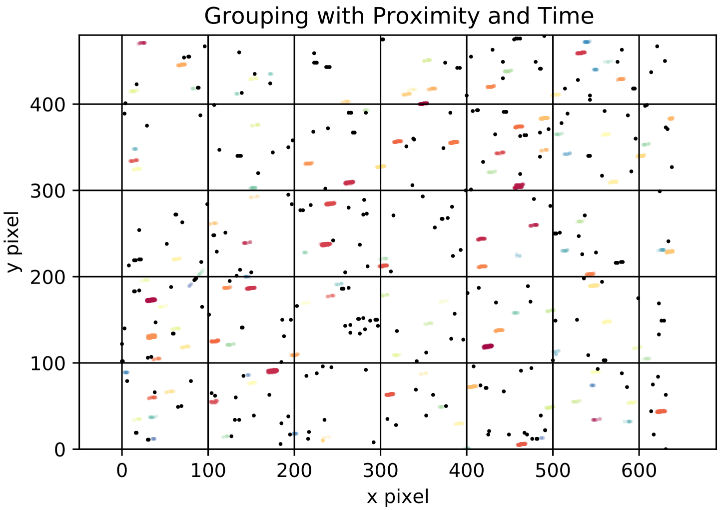
- Classic Post Processing
  1. Integrate data over 3 second time slice FITS image
  2. SExtractor yields: $(column, row, flux)$
  3. Conversion of flux to visual magnitude: $(column, row, v_{mag})$
  4. Astrometry.net maps $(column, row)$ to (RA, DEC) and identifies reference stars and satellites
  5. Correlate satellite (RA, DEC) from each time slice with a satellite detection

- New Temporal Data Association
  1. Cluster data in 3-dimensions
  2. Filter clusters with too few pixels and/or events
  3. Combine clusters with Hough transform
  4. Assign cluster numbers to satellites
  5. Extract signature and temporal characteristics

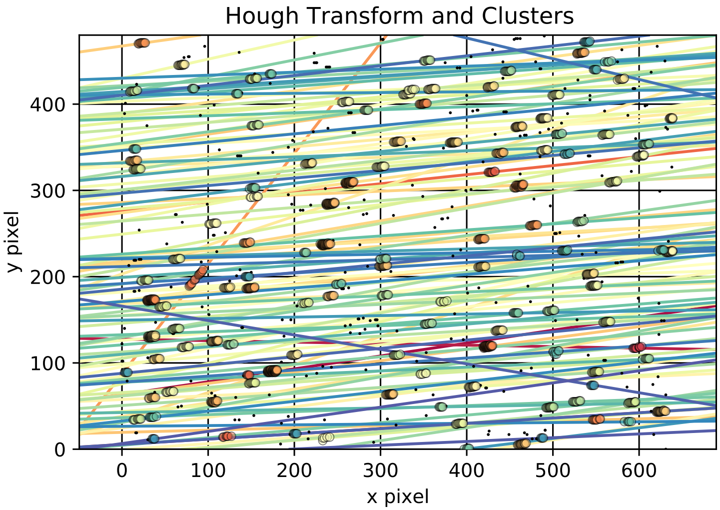
Clustering


a) Density Clustering
b) Time Sequential Clustering
y
x
t
x
t
y
t
x
y
x
t
x
t
y
t

Clustering

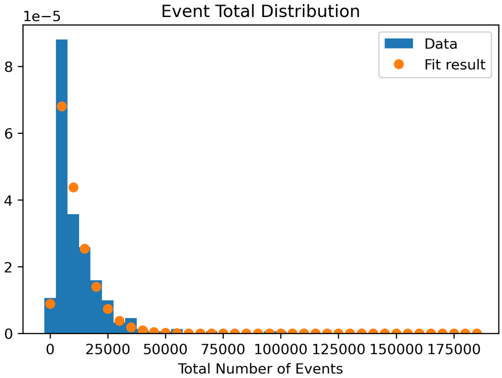

Grouping with Proximity and Time
400
300
200
100
0
y pixel
0
100
200
300
400
500
600
x pixel

Hough Transform

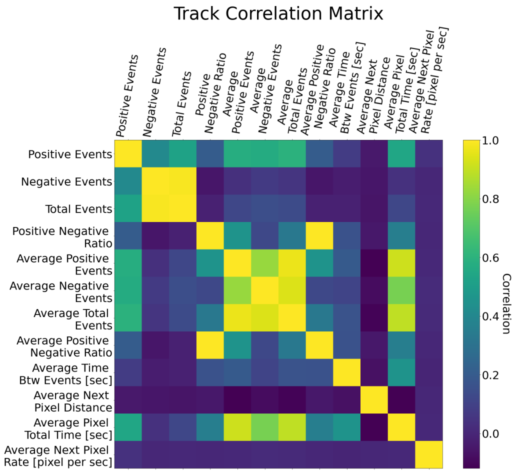


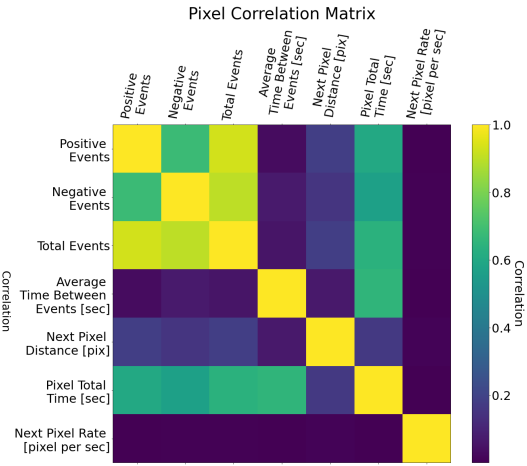
New Approach Limitations

- Human involvement is necessary
  - Easier to access in 2-dimensions
  - Poor signal to noise datasets are hard to process
- Time clustering is more consistent, but slow

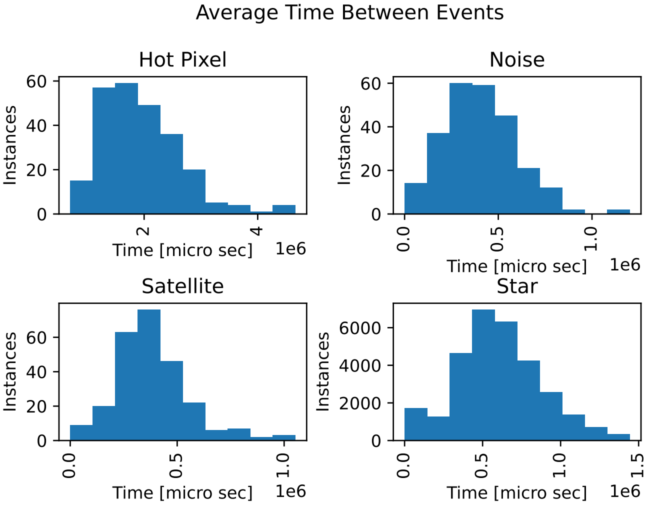


Selected Characteristics





Characteristic Distributions



Validation Plan

1. Select at random a set of data from those post-processed
2. Simulate the physics front-end once
3. Run sensitivity analysis on camera parameters
4. Create Jacobian from sensitivity analysis
5. Find least squares fit of camera parameters
6. Use best fit parameters to simulate other collections
7. Compare the distributions with the Kolmogorov Smirnov Test

Non-linear Least Squares

- Sensitivity analysis is a finite difference approximation
- Produces Jacobian, J_{ij}

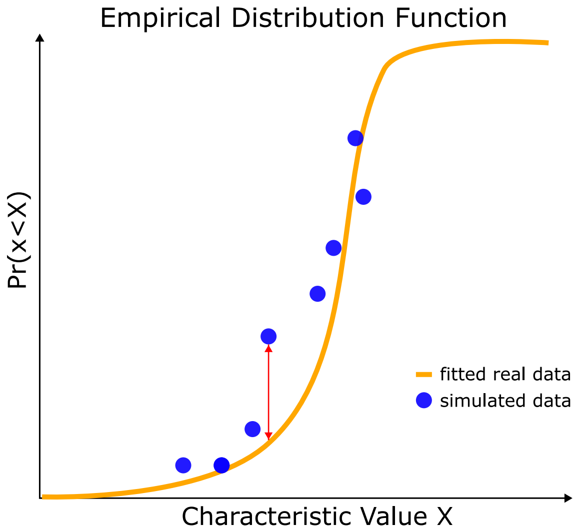
$$J_{ij} = -\frac{\delta r_i}{\delta \beta_j}$$

  - Residuals, r_i
  - Input Parameters, β_j
- Least Squares to find change in output, Δy

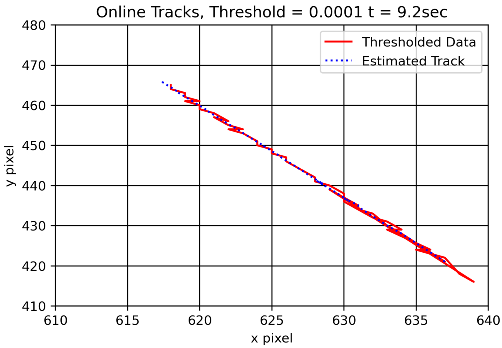
$$(J^T J)\Delta\beta = J^T \Delta y$$

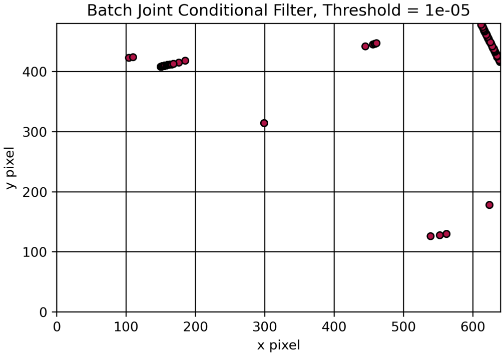
$$\begin{bmatrix} \frac{\delta r_1}{\delta \beta_1} & \frac{\delta r_1}{\delta \beta_2} & \cdots & \frac{\delta r_1}{\delta \beta_j} \\ \frac{\delta r_2}{\delta \beta_1} & \frac{\delta r_2}{\delta \beta_2} & & \\ \vdots & & \ddots & \vdots \\ \frac{\delta r_i}{\delta \beta_1} & & \cdots & \frac{\delta r_i}{\delta \beta_j} \end{bmatrix}$$

Kolmogorov Smirnov Test

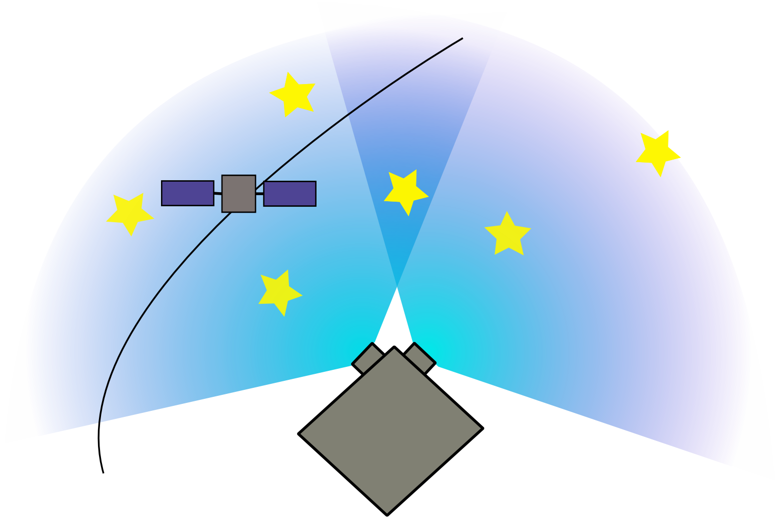


Multiple Hypothesis Tracker





Event-based Sensor Star Tracker



Other Projects

- Incorporation into an optical neural network
  - Recurrent Neural Network
  - Spiked Output
- Low light noise while slewing characteristic study
- Clustering algorithm update to analyze event-based data of lightning

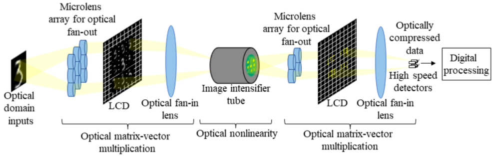


Figure: Sohani, 2021, NDSEG Proposal

Contribution Overview

- Code: Event-based Sensor Model for Space Domain Awareness, various modules (physics front end, scaling white noise, limited arbiter)
- Conference Paper: Event-based Sensor Model for Space Domain Awareness, Advanced Maui Optical and Space Surveillance Technologies Conference 2021
- Code: Event-based post processing clustering algorithm for data association
- Code: Event-based multiple hypothesis tracker
- Conference Paper: Event-Based Sensor Multiple Hypothesis Tracker For Space Domain Awareness, Advanced Maui Optical and Space Surveillance Technologies Conference 2022
- Conference Short Course: An Introduction to Event-Based Sensors for SDA: A Hands-On Tutorial, Advanced Maui Optical and Space Surveillance Technologies Conference 2022

Contribution Overview Continued

- Research Seminar: Finding Satellites in Event-based Data, SGRS 2022
- Journal Paper: Verification of a Satellite Observing Event-Based Sensor Model, To Be Submitted in September 2022

Thank you for listening!

Special thank you to my committee members, husband, and friends for their never-ending patience with me.

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Backup Slides - Courses Taken

- For Credit
  - AEP 5400 - Nonlinear and Quantum Optics
  - MAE 5180 - Autonomous Mobile Robots
  - MAE 5730 - Intermediate Dynamics
  - MAE 5780 - Feedback Control Systems
  - MAE 5830 - Astronautic Optimization
  - MAE 6760 - Model-Based Estimation
  - MAE 6780 - Multivariable Control Theory
- Audited
  - MAE 6280 - Adaptive and Learning Systems
  - MAE 6700 - Advanced Dynamics
  - CS 5780 - Intro to Machine Learning

Backup Slides - Additional Graduate Level Courses

- Taken at the Air Force Institute of Technology
  - Linear Systems Analysis
  - The Space Environment
  - Methods of Applied Mathematics
  - Intermediate Dynamics
  - Space Mission Analysis and Design
  - Satellite Communications
  - Control and State Space Concepts
  - Introduction to Flight Dynamics
  - Applied Linear Alegbra
  - Intermediate Space Flight Dynamics
  - Spacecraft Systems Engineering
  - Satellite Design and Test
  - Modern Methods of Orbital Determination
  - Space Surveillance
  - Chemical Rocket Propulsion

Backup Slides - Irradiance Calculations

- Star by Johnson V: $V_0 = q_v - 2.5log(F_v)$
  - q_v zero magnitude flux scaled from Vega
  - Rearrange Equation for Flux
  - $F_v = 10^{-0.4(V_0 - q_v)}[\frac{W}{cm^2 Angstrom}]$
  - Multiply by bandpass, filter width, and recieving area
  - $P_v = F_v Area Bandpass$
- Satellite by Point Source:
  - Power sent to hemisphere
  - $I = \frac{L \sum(A_{surf} \rho_{surf})}{2 * \pi}$
  - Calculate energy recieved per steradian
  - $\mathcal{E}_\lambda = \frac{I_\lambda * cos(\theta_R)}{R^2}$
  - Multiply by receiving area
  - $P_{sat} = \mathcal{E}_\lambda Area$

Backup Slides - Zernike Mode Weighting

$$Z_{evenj} = \sqrt{n+1}R_n^m(r)\sqrt{2}cos(m\theta)$$
$$Z_{oddj} = \sqrt{n+1}R_n^m(r)\sqrt{2}sin(m\theta)$$
$$Z_j = \sqrt{n+1}R_n^0(r), m = 0$$

$$\Theta_{atm}(r,\theta) = \sum_j a_j Z_j(r,\theta).$$

$$C_{j,j'} = E[a_j, a_{j'}] = \frac{K_{zz'}\delta_z\Gamma[(n+n^{'}-5/3)/2](D/r_o)^{5/3}}{\Gamma[(n-n'+17/3)/2]\Gamma[(n'-n+17/3)/2]\Gamma[(n+n'+23/3)/2]}.$$

$$a_j = U^T \cdot \overrightarrow{n}.$$

Backup Slides - Beta Binomial Distribution Fit

- Unknown or random probability of success in each of a fixed or known number of Bernoulli trials
- Binomial distribution modification: probability of success is drawn from beta distribution
- Fit with selection of approximate α and β values defining the continuous beta distribution
- Defined the bin size and center values of those bins
- Curve fit the center locations to a continuous beta distribution

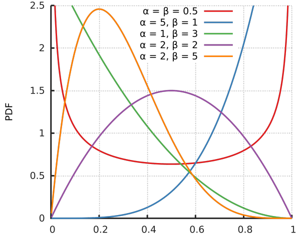

Figure: Horas, 2014